DIGITAL INEQUALITY: GENDER-BASED EPISTEMIC BIAS IN ARTIFICIAL INTELLIGENCE SYSTEMS

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Abstract

Digital inequality is otherwise referred to as coded inequality. It refers to the hidden or systematic forms of bias and discriminations entrenched in digital techs and algorithms which produce or amplify social inequalities under the guise of neutrality or objectivity. Coded inequality is the latest gender-based bias humanity contends with in Artificial Intelligence systems (AI). AI, long championed as a neutral tool for rational decision-making, increasingly reflects and reinforces gendered inequalities. This paper interrogates the origins, manifestations and ethical implications of gender bias in AI technologies with the critical periscopes of feminism and intersectional epistemologies; it reveals how biased data, algorithmic opacity and gendered labour structures embed patriarchal values into AI systems. The paper adopts the philosophical expository method to analyze typical practices and issues associated with digital techs operations. The expository analysis demonstrates how AI technologies often reproduce social hierarchies under the guise of efficiency. Ethical and epistemological reflections grounded in feminist care ethics, situated knowledge and decolonial feminism challenge the prevailing techno-rationalist paradigm. Finally, the paper outlines a pathway towards feminist AI futures, rooted in participatory design, intersectional data governance, legal reform and inclusive digital literacy. Rather than rejecting AI outright, it calls for its radical transformation through a justice-oriented framework that centers lived experience, accountability and global plurality.

KEYWORDS: AI Systems, Algorithmic Bias, Epistemic Bias, Gendered Inequalities, and Techno-Rationalist Paradigm.

INTRODUCTION

The contemporary global society is plagued by social malaises of racism, ethnicism, classism, lookism, ableism, religionism and genderism (sexism). These social inequalities and inordinate discriminations are based on prejudice. The most pertinacious, outrageous, divisive and ubiquitous of these social discriminatory stereotypes is genderism (sexism). Genderism consists of the subversion and displacement of biological identity with social binary identities, relations, roles and rules, thereby reconfiguring the social world into a gendered world. This is the causal factor responsible for the prevailing global gender fissure.[1] The digital world entrenches and perpetuates this gender-based bias.

This philosophical treatise which draws insights from applied ethics, social epistemology, feminism and philosophy of technology (AI), explores the phenomenon of coded gender-based inequalities is in AI systems. Apparently, it might be plausible to assume that Artificial Intelligent Systems mirror gender-based epistemological bias. The accelerating integration of artificial intelligence (AI) into daily life, from healthcare algorithms and recruitment platforms to social media moderation and virtual assistants; has sparked significant debate over the impartiality of these technologies. While AI is often framed as a neutral and rational tool, research increasingly reveals that it can reflect, reproduce and even amplify human biases, particularly gender-based ones. The phenomenon of gender bias in AI systems has emerged as a major concern among ethicists, computer scientists, feminists and policymakers. This has implications that span justice, employment, healthcare and democratic participation.

We are in a digital age where algorithms increasingly influence who gets a job, who receives medical attention, or whose voice is heard. The embeddedness of gender norms in machine learning models cannot be underestimated. As Safiya Umoja Noble warns, "Algorithms are not objective or neutral, rather they are reflections of the priorities, preferences and biases of the people who build them".[2] AI's purported rationality often conceals the data-driven inheritance of sexist assumptions. For instance, recruitment AI trained on decades of hiring data may learn to favour male candidates, while image-recognition systems might more frequently misclassify women of colour.

This paper interrogates the ways in which AI systems both reflect and reinforce gender inequality. It traces the sources of algorithmic bias, explores key case studies where gender bias has had real-world consequences. It further discusses the epistemological and ethical frameworks required to counteract such inequities. The ultimate aim is not to reject AI as inherently flawed, but to critically examine the gendered assumptions beneath its design and implementation and to propose ways of cultivating feminist, anti-discriminatory and inclusive approaches to AI development.

THE ORIGIN OF ALGORITHMIC GENDER BIAS

To understand gender bias in AI systems, one must first confront the myth of technological neutrality. AI fundamentally relies on data and algorithms. These are sets of instructions designed to solve problems or make decisions. However, these inputs and processes do not exist in a vacuum, they are embedded in human histories, social systems and cultural norms. Gender bias in AI arises not from a malfunction of the machine, but from the structural inequalities and epistemic assumptions encoded into the data it consumes and the logic it follows.

BIASED DATA SITES: THE HISTORICAL INHERITANCE OF DISCRIMINATION

AI systems (particularly those using machine learning), depend on vast quantities of historical data to learn patterns. Yet much of this data reflects decades, if not centuries, of gendered discrimination. For example, a recruitment algorithm trained on résumés submitted

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[1] Falana, Christiana Titi and Uzomah Maduawuchi Uzomah, *Feminimasculinism*: *Integrated Science of Gender Fissure*, (Kaduna: All-Well Printing and Publishing Company, 2024), p. x.

[2] Safiya Umojo, *Algorithms of Oppression: How Search Engines Reinforce Racism*, (New York: New York University Press), p. 5.

to a tech company over the past ten years may learn that most successful candidates were male. This enables the system to rank male applicants higher, even for gender-neutral positions. In a widely publicized case, Amazon had to scrap its AI hiring tool after discovering it penalized applications that included the word "women's," such as "women's chess club captain".[3] This phenomenon is not accidental. As Ruha Benjamin argues, "When machine learning systems train on biased data, they codify past discrimination into future decision-making".[4] The result is a form of automated injustice in which the past is not merely remembered but replicated.

ALGORITHMIC DESIGN AND IMPERVIOUS REASONING

Even when datasets are carefully curated, the logic of the algorithm itself can produce gendered outcomes. Developers make numerous decisions about what variables to include, how to weigh them and what goals to optimize for. These decisions, often made without interdisciplinary consultation, can entrench assumptions about gender roles and expectations. For instance, if an algorithm is trained to predict leadership potential based on traits like assertiveness and dominance, it may undervalue women who are often socially penalized for exhibiting the same traits that are rewarded in men.[5] This of course is a conspicuous example of coded inequality.

Compounding the issue is the "black box" nature of many AI systems, particularly deep learning models. These systems generate decisions that are difficult, if not impossible, to fully explain. As a result, individuals affected by gender-biased decisions, whether denied a loan, a job, or medical treatment, may have no recourse, and developers may not fully understand the discriminatory pathways their models have constructed.

GENDERED LABOUR IN AI DEVELOPMENT

Another root cause of algorithmic gender bias lies in the tech industry itself. AI is largely built by male-dominated teams operating within organizational cultures that often lack gender diversity and sensitivity. A 2023 UNESCO report found that only 22% of AI professionals globally are women.[6] This lack of representation has real consequences. Virtual assistants like Siri, Alexa and Google Assistant were originally programmed with female voices and deferential personalities. This portrays women as complainants, help mates and subordinates.[7] Moreover, much of the invisible labour that supports, AI, such as data annotation, content moderation and digital cleaning, is outsourced to poorly paid workers in the Global South, many of whom are women. These workers often face exploitative conditions and are rarely credited for their roles in shaping the systems we use daily.[8] Thus, gender bias is not only embedded in AI's outputs but also in the global division of labour that enables its development.

EPISTEMIC INJUSTICE IN AI KNOWLEDGE SYSTEMS

[3] Jeffrey Dastin, "Amazon Scraps Secret AI Recruiting Tool That Showed Bias Against Women". *Reuters*, 10 Oct. (2018), p. 20. www.reuters.com/article/us-amazon-com-jobs-automation-insight-idUSKCN1MK08G.

[4] Ruha Benjamin, *Race After Technology: Abolitionist Tools for the New Jim Code*, (Polity Press, 2019), p.89.

[5] Joan C Williams and Rachel Dempsey, *What Works for Women at Work: Four Patterns Working Women Need to Know*, (NYU Press, 2014), p. 109

[6] UNESCO, www.unesco.org/reports.12

[7] Mark West, et al. *"I'd Blush If I Could: Closing Gender Divides in Digital Skills Through Education*", (UNESCO, 2019), p.9.

[8] Mary L. Gray and Siddharth Suri, *Ghost Work: How to Stop Silicon Valley from Building a New Global Underclass*, (Houghton Mifflin Harcourt, 2019), p. 56.

Drawing from Miranda Fricker's concept of epistemic injustice, we can see that AI systems often perpetuate both testimonial and hermeneutical injustice. Testimonial injustice occurs when women's voices or data are undervalued or excluded, while hermeneutical injustice arises when dominant social groups control the meaning-making processes that shape how problems are understood. In AI, the absence of female and non-binary experiences in training data or model evaluation frameworks constitutes a form of epistemic exclusion.[9] For example, many natural language processing (NLP) systems have been found to associate terms like "doctor" or "engineer" with male pronouns, while linking "nurse" or "teacher" to female ones. These linguistic biases not only mirror typical societal stereotypes but also affect how machines interpret and reproduce language. This reinforces the very discourses that feminist theory has long challenged.

EMPIRICAL STUDIES IN GENDERED AI BIAS

Concrete case studies are crucial for understanding how gender bias in artificial intelligence manifests in real-world systems. From flawed facial recognition to discriminatory healthcare algorithms, the impact of AI is often obscured by its technical complexity and the opacity of proprietary systems. This section explores specific instances where AI technologies have produced or exacerbated gender disparities. It offers insights into the structural, technical and ethical implications of algorithmic design.

1. Gender Bias in Facial Recognition Technology

One of the most significant and alarming cases of gender bias in AI is found in facial recognition technologies (FRT). Joy Buolamwini's groundbreaking work with the MIT Media Lab's Gender Shades project revealed that facial analysis algorithms from major tech companies like IBM, Microsoft and Amazon performed significantly worse on darker-skinned women than on lighter-skinned men.[10] For example, while lighter-skinned males were classified with near-perfect accuracy (99%), error rates for darker-skinned females reached as high as 34%. This disparity arises from training data that is overwhelmingly composed of white male faces. This influences the algorithms to underperform on individuals who deviate from this "norm". Buolamwini called this the "coded gaze", a term that describes the social and cultural biases embedded in algorithmic systems. The consequences of such disparities are not academic: facial recognition systems are increasingly used in policing, immigration and surveillance. This places marginalized groups, especially women of colour at disproportionate risk of misidentification and profiling.

2. Discriminatory Hiring Algorithms

Another widely cited example is Amazon's AI recruitment tool, which was designed to automate the screening of résumés. Trained on ten years of data from predominantly male applicants, the system began to downgrade résumés that included words like "women's," as in "women's chess club captain".[11] It also penalized graduates of all-women's colleges and overvalued male-coded language and work experiences. The tool not only reflected but amplified systemic biases in hiring practices. Amazon eventually abandoned the system, however, the case underscores a broader concern: when AI is trained on biased human behaviour, it tends to learn and replicate discrimination. Moreover, the opacity of such systems

[9] Miranda Fricker, *Epistemic Injustice: Power and the Ethics of Knowing*, (Oxford UP, 2007), p. 13.

[10] Joy Buolamwini and Timnit Gebru. "Gender Shades: Intersectional Accuracy Disparities in Commercial Gender Classification", *Proceedings of Machine Learning Research*, vol. 81, (2018), p. 77.

[11] Jeffrey Dastin, "Amazon Scraps Secret AI Recruiting Tool That Showed Bias Against Women". *Reuters*, 10 Oct. (2018), p. 20. www.reuters.com/article/us-amazon-com-jobs-automation-insight-idUSKCN1MK08G.

can make it difficult for candidates to understand why they were rejected. This unfortunately denies them procedural fairness and recourse.

3. Gendered Voice Assistants and the Reinforcement of Stereotypes

Many of today's virtual assistants such as Apple's Siri, Amazon's Alexa, Microsoft's Cortana and Google Assistant, default to female voices and exhibit servile personalities. In earlier versions, these systems would respond flirtatiously or submissively to sexually explicit commands. This prompted criticism from feminist scholars and technologists alike. As UNESCO notes in its report titled, "I'd Blush If I Could", such interactions "project a digitally encrypted version of real-world gender biases".[12] These design choices are not trivial. Tech companies perpetuate the stereotype of women as always available to serve, answer and please. They forge female personas in roles that are subservient, accommodating and non-confrontational. Even when developers offer the option of a male voice, the default tends to be female, signaling an implicit norm.

Although some companies have responded to criticism by modifying responses to harassment or offering gender-neutral voices as Google did with its "Q" voice, yet the deeper issue remains unresolved. The projection of gender onto AI systems is rarely neutral and often reinforces the cultural scripting of femininity as service-oriented and emotionally laborious.

4. Bias in Healthcare Algorithms

Healthcare is another domain where AI-driven gender bias can have life-or-death consequences. In a 2019 study published in Science, Obermeyer et al. found that an algorithm used to manage healthcare for over 200 million patients in the United States systematically underestimated the health needs of Black patients compared to white patients with similar conditions. While this study focused primarily on racial disparities, it illuminated a broader problem: algorithms that prioritize cost-efficiency or historical spending data often ignore the structural inequities that affect women and minorities.

For women, particularly those from marginalized racial or socio-economic backgrounds, such systems can exacerbate disparities in diagnosis, treatment and care prioritization. Moreover, women are historically underrepresented in clinical trial data, which forms the basis for many AI-powered medical tools. As a result, AI systems trained on male-centric data may fail to accurately assess conditions that present differently in women, such as heart disease or autoimmune disorders.[13]

5. Content Moderation and the Silence of Feminist Speech

Social media platforms use AI and machine learning algorithms to moderate content at scale. While these systems are designed to remove hate speech, misinformation and explicit material, they frequently misidentify feminist or LGBTQ+ content as offensive, while allowing actual misogynistic or homophobic content to remain.[14] This asymmetry is especially dangerous in authoritarian contexts where governments may use platform moderation policies to suppress dissent. For instance, feminist activists in countries like Iran or Uganda have reported that their posts are disproportionately removed or shadow-banned, even when they do not violate community standards.

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[12] Cited in Michael Maduawuchi Uzomah, *Fundamental Issues in Gender Studies*, (Kaduna, E-mesh Printing Press, 2017), 20..

[13] Perez Criado Caroline, *Invisible Women: Data Bias in a World Designed for Men*, Abrams (Press, 2019), p. 199.

[14] Tarleton Gillespie, *Custodians of the Internet: Platforms, Content Moderation, and the Hidden Decisions That Shape Social Media*, (Yale UP, 2018), p. 121.

The lack of transparency in moderation algorithms means that users often do not know why content was removed, and there is little opportunity for appeal. Hence, rather than amplifying marginalized voices, content moderation algorithms can contribute to epistemic silencing. This happens where feminist knowledge and experience are rendered invisible in the digital public sphere.

The above case studies demonstrate that gender bias in AI is not hypothetical or isolated. It is systematic, endemic, pervasive and deeply embedded in the datasets, design choices and institutional cultures that shape how AI technologies function. Whether in recruitment, healthcare, law enforcement, or everyday digital interactions, AI systems often replicate the very inequalities they are assumed to transcend. Confronting these issues requires a rigorous interdisciplinary approach. It requires an approach that brings together technical knowledge with feminist, ethical and decolonial insights.

ETHICAL AND EPISTEMOLOGICAL REFLECTIONS ON GENDER AND AI

Understanding and confronting gender bias in artificial intelligence requires more than technical fixes. It necessitates a robust ethical and epistemic inquiry into how knowledge is produced, who produces it and whose values and experiences are prioritized in digital infrastructures. AI, while mathematical and computational in function, is also deeply philosophical in consequence. This section draws on feminist ethics, postcolonial epistemologies and the philosophy of technology to analyze the deeper implications of AI's gendered logic.

The Myth of Objectivity: Gendered Epistemologies in Techs

At the heart of AI development lies a powerful but flawed assumption. The assumption holds that data and algorithms are neutral tools for rational decision-making. This epistemological posture, inherited from Enlightenment rationalism and positivist science, privileges abstraction, quantification, and control values historically associated with masculinist forms of knowledge.[15] In practice, this has meant sidelining forms of experiential, emotional or relational knowledge often associated with women and other marginalized groups.

Feminist epistemologists such as Sandra Harding and Donna Haraway have long critiqued the "god trick" of disembodied objectivity, where the knower claims to observe the world without being embedded in it.[16] In AI contexts, this translates into models that claim universality while being trained on partial exclusionary data sets. Haraway's call for "situated knowledges" becomes crucial: knowledge production, including technological design, must recognize its standpoint and positionality.

The central argument of this paper is that when AI systems ignore the social context of data, they risk naturalizing structural inequalities. For instance, using arrest records to predict criminal behaviour may seem neutral. However, if those records are shaped by racially and gender-bias policing, then the algorithm will not just reflect bias, it will also operationalize it.

Ethics of Care and Relational AI Design

Dominant AI ethics frameworks often developed within corporate or technocratic circles emphasize abstract principles such as fairness, accountability, transparency and privacy. While important, these frameworks may overlook the relational, emotional and embodied

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[15] Sandra Harding, *The Science Question in Feminism*, (Cornell UP, 1986). p/ 3.

[16] Donna Haraway, "Situated Knowledges: The Science Question in Feminism and the Privilege of Partial Perspective", *Feminist Studies*, vol. 14, no. 3, (1988), pp. 575–599.

dimensions of ethical life. The feminist philosopher, Virginia Held proposes an alternative: the ethics of care, which centers on responsiveness, dependency and interconnection as foundational to moral reasoning.[17]

Applying care ethics to AI design shifts the focus from individual rights to collective responsibilities. It urges developers to ask: How will this technology affect the most vulnerable users? Who bears the burden when AI fails? How can systems be designed to foster empathy rather than surveillance, support rather than control? For example, AI systems used in domestic violence prevention must go beyond risk prediction models to engage with survivors' lived experiences, prioritize safety and dignity and incorporate feedback loops for care-based decision-making. Similarly, educational AI tools should be sensitive to gendered learning styles and barriers, rather than enforcing standardized metrics of performance.

DECOLONIAL FEMINISM AND THE GLOBAL POLITICS OF AI

Gender bias in AI does not exist in isolation from global power dynamics. The datasets, algorithms, and labour that power AI systems are often sourced from or imposed upon populations in the Global South without consent, context or benefit. Decolonial feminists such as Sylvia Tamale and Ochy Curiel emphasize that Western models of gender and technology often erase indigenous epistemologies and ontologies.[18] In this sense, AI can become a digital instrument of epistemic colonialism replicating what Walter Mignolo calls the "coloniality of power" in computational form.[19]

For instance, biometric surveillance technologies exported from Silicon Valley to African states under the guise of development can reinforce patriarchal control, violate privacy and marginalize gender-nonconforming individuals. These systems often ignore local understandings of identity, community and gender fluidity in favour of rigid binary classification schemes. Ethical AI, then, must be not only gender-aware but also geopolitically attuned. It must ask: Whose knowledge systems are legitimized in global tech governance? Who gets to define ethical standards? And how can we design AI that honours plural, intersectional and indigenous visions of justice?

TESTIMONIAL AND HERMENEUTICAL JUSTICE IN AI ETHICS

Building on Miranda Fricker's notion of epistemic injustice, we can frame AI bias as both a testimonial and hermeneutical failure. Testimonial injustice occurs when the testimony of certain social groups, such as women, LGBTQ+ people, or disabled individuals, is systematically devalued. In AI, this manifests when their data is underrepresented, their feedback is ignored, or their needs are deprioritized in design processes.[20]

Hermeneutical injustice, by contrast, arises when marginalized groups lack the conceptual resources to make sense of their experiences, often because dominant institutions fail to recognize or articulate their realities. In AI contexts, this may involve the lack of adequate categories for non-binary identities, the erasure of context-specific forms of oppression, or the refusal to acknowledge emotional labour as quantifiable input.

To counter these injustices, AI ethics must move beyond liberal inclusion toward radical co-creation. This involves inviting affected communities into the design, testing and

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[17] Virginia Held, *The Ethics of Care: Personal, Political, and Global*, (Oxford UP, 2006). P. 15.

[18] Sylvia Tamale, *Decolonization and Afro-Feminism*, (Daraja Press, 2020), p. 119.

[19] Walter D. Mignolo, "The Geopolitics of Knowledge and the Colonial Difference", *South Atlantic Quarterly*, vol. 101, no. 1, (2002), pp. 57-96.

[20] Fricker, p. 17.

evaluation of AI systems not as passive recipients of technology, but as epistemic agents capable of shaping its values and goals.

Ethics in AI is not just a matter of tweaking code or patching data; it is a philosophical and political task that requires rethinking the foundations of how we know, value and relate. Gender bias in AI systems is a symptom of deeper epistemological hierarchies that privilege abstract objectivity over situated knowledge, disconnection over care and Western rationalism over global plurality. We can begin to imagine and build AI systems that are not only smarter, but wiser, fairer and more humane drawing insights from feminist ethics, decolonial thought and epistemic justice frameworks.

TOWARDS INCLUSIVE FEMINIST AI FEATURES

As the ethical implications of gender bias in AI gain visibility, there is growing urgency to envision and implement inclusive frameworks that resist the reproduction of patriarchal, racial and colonial hierarchies. A truly transformative AI future requires the integration of feminist theory, participatory design, intersectional data governance and global epistemic justice. This final section offers pathways for designing feminist AI technologies that are not only technically robust, but socially emancipatory, culturally sensitive and ethically grounded.

Feminist Human-Computer Interaction and Participatory Design

Feminist contributions to the field of human-computer interaction (HCI) emphasize the relational, contextual and experiential dimensions of technology use. Shaowen Bardzell argues that feminist HCI "foregrounds users' voices, emotions and lived experiences," especially those of women and marginalized groups, in the design process.[21] This approach contests the dominant "design from above" paradigm by advocating for participatory methodologies that treat users as co-creators rather than passive consumers.

In practice, this might involve conducting gender-sensitive needs assessments before system design, ensuring linguistic and cultural diversity in voice AI applications, and designing user interfaces that consider accessibility for trans and non-binary individuals. It also requires challenging the masculinist culture within tech development teams, like cultures that often dismiss emotional expression, empathy or social embeddedness as irrelevant to innovation.

Participatory feminist design creates space for intersectional inclusion, allowing for a multiplicity of identities, experiences and power dynamics to shape technological outcomes. Such approaches not only correct for bias but open up new epistemological and ethical horizons in AI development.

Intersectional Data Governance

It is germane to assert that Kimberlé Crenshaw's theory of intersectionality is indispensable to the construction of equitable AI systems. Intersectionality posits that individuals experience overlapping and interdependent systems of oppression, such as racism, sexism, ableism and classism, which cannot be understood in isolation.[22] An AI system that

[21] Shaowen Bardzell, "Feminist HCI: Taking Stock and Outlining an Agenda for Design", *Proceedings of the SIGCHI Conference on Human Factors in Computing Systems*, (2010), p. 1306.

[22] Kimberlé Crenshaw, "Mapping the Margins: Intersectionality, Identity Politics, and Violence Against Women of Color", *Stanford Law Review*, vol. 43, no. 6, (1991), p. 140.

only considers gender, without accounting for race, class, or disability, will fail to capture the full complexity of discrimination.

Current practices in data collection and governance are often inadequate in this regard. Training datasets may erase intersectional identities by flattening gender into binary categories or ignoring cultural context. Moreover, anonymized data frequently strips individuals of their social positioning, producing abstract "users" whose needs do not reflect real-world structural inequities.

To address this, AI development must adopt data practices grounded in justice and transparency. Projects like the Data Feminism framework by Catherine D'Ignazio and Lauren Klein offer practical tools for intersectional data work, including reflexive documentation, community-led annotation and power-aware modeling techniques.[23] These practices seek not just to protect individual privacy but to redress collective harm and foster equity.

Policy and Legal Frameworks for Gender-Just AI

While grassroots innovation and academic critique are essential, systemic change in AI also requires robust policy and legal interventions. Governments, international organizations and tech corporations must commit to binding standards that address gender bias and discrimination in algorithmic systems.

The European Union's proposed AI Act is a step toward regulating high-risk AI systems, but feminist legal scholars argue that it must go further by incorporating gender impact assessments and accountability mechanisms.[24] Similarly, in African contexts, regional frameworks such as the African Union's Digital Transformation Strategy should explicitly address algorithmic harms through gender-sensitive digital policies and data protection laws.

Legal frameworks should ensure transparency in AI decision-making, mandate diverse stakeholder consultation in design and deployment, and create enforceable penalties for discriminatory outcomes. Importantly, policy responses must avoid technological determinism. The latter is the belief that better code alone can fix structural injustice. Instead, they should center social justice, historical redress and community empowerment as essential components of ethical AI.

Education, Culture and the Reimagining of Technological Features

Beyond legal and technical reform, building feminist AI futures requires cultural transformation. This means fostering digital literacies that empower users to question, critique and shape the technologies they interact with. It also means revising curricula in computer science, engineering and data science to include feminist theory, critical race studies and decolonial thought.

Initiatives like AI4ALL and Data+Feminism Lab model how inclusive educational environments can bridge the gap between STEM and the humanities. Popular media and the arts also play a vital role in challenging dominant techno-utopian narratives and imagining alternative technological futures.

In African and Global South contexts, reimagining AI must involve recovering indigenous philosophies that emphasize relationality, reciprocity and communal well-being.

[23] Catherine D'Ignazio, and Lauren Klein, *Data Feminism*, (MIT Press, 2020), p. 25.
[24] AI Now Institute, *Confronting Black Boxes: A Shadow Report on the EU AI Act*, (2021), www.ainowinstitute.org.

Ubuntu, for instance, offers a counter-logic to individualistic and extractive models of innovation. As Achille Mbembe writes, "Technology should serve life, not the other way around".[25] Feminist AI futures, therefore, are not about perfecting machines, but about reclaiming the human, social and planetary values that technology should serve.

A feminist approach to AI is not merely a call for better inclusion or fewer errors. It is a transformative vision that questions the foundations of knowledge, power and design. Through centering lived experience, relational ethics and intersectional justice, feminist AI futures offer the possibility of building systems that do not merely reflect the world as it is, but imagine the world as it could be. In confronting the gender biases coded into our machines, we take a step toward reclaiming technology for liberation, rather than oppression.

Summary and Conclusion

Coded inequalities reveal how digital systems often mirror the same divisions and hierarchies that already exist in society. Far from being neutral, algorithms and data infrastructures can quietly encode bias into everyday processes in aspects such as access to education, job opportunities, healthcare, or even civic participation. What makes this troubling is not only the scale at which such inequalities spread, but also the hidden nature of their operation. People interact with technology believing it to be objective, when in reality it may be amplifying structural injustice in subtle but far-reaching ways.

Recognizing these patterns calls for both vigilance and responsibility; designers, policymakers, and everyday users must resist the temptation to see technology as above human values, and instead engage it critically as a social tool that reflects choices and priorities. By questioning how data is gathered, who codes the systems, and whose voices are excluded, we move closer to building technologies that serve justice rather than entrenching division. The challenge is significant, but so is the opportunity to ensure that the digital future is guided by fairness, inclusivity, and shared humanity. Ultimately, our task is to shape technology not as a mirror of our inequalities, but as a mirror of our highest ideals.

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